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Improving the assessment and reporting on rare and endangered species through species distribution models

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ABSTRACT

Species distribution models (SDMs) are increasingly used to understand rare and endangered species distributions, as well as the environmental pressures affecting them. Detailed knowledge of their distribution is critical for reporting its conservation status, and SDMs are potential tools to provide the relevant information to conservation practitioners. In this study, we modeled the distribution of *Veronica micrantha*, a vulnerable plant whose conservation status has to be periodically assessed under Article 17 of the Habitats Directive.

The objective was to highlight the potential of SDMs for the assessment of threatened species within the periodical report on their conservation status. We used a spatially explicit modeling approach, which predicts species distributions by spatially combining two SDMs: one fitted with climate data alone and the other fitted solely with landscape variables. A comparison between the modeled distribution and the range obtained by classical methods (minimum convex polygon and *Range Tool*) is also presented. Our results show that while data-based approaches only consider the species known distribution, model-based methods allow a more complete evaluation of species distributions and their dynamics, as well as of the underlying pressures. This will ultimately improve the accuracy and usefulness of assessments in the context of EU reporting obligations.

1. Introduction

Halting the decline of biodiversity worldwide is acknowledged as one of the greatest challenges facing Humanity (CBD, 2010) and achieving this will require an unprecedented effort (Wolinsky, 2011). In the European context, the EU reporting obligations under the Article 17th of the Habitats Directive (92/43/EEC) resulted from the pressing need to assess the overall conservation status of species and habitats of community interest (European Commission, 1992). Habitats Directive aims to promote the maintenance of biodiversity by requiring Member States (MS) to take measures to maintain or restore natural habitats and wild species listed on the Annexes to the Directive at a favorable conservation status, introducing robust

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protection for those habitats and species of European importance. MS are thus required to report every six years, providing extensive data regarding the conservation status of species and habitats classified as favorable, inadequate, unfavorable, or unknown. Reporting includes several relevant parameters for species assessment such as range, number and dimension of populations, suitable habitat and future prospects (ETC/BD, 2011). Overall, as a result from the 2007 report, a significant percentage of species (27%) and habitats (13%) was considered to be data deficient, meaning that the information available does not allow the assessment of their conservation status (European Commission, 2009). Further, the lack of data is more acute in southern countries, such as Portugal and Spain, where more than 50% of the species assessments were classed as 'unknown'.

Rare species may be at greater risk of extinction because of their small geographic ranges, low abundances, and greater susceptibility to environmental changes (Pimm et al., 1995; Broennimann et al., 2005; Lavergne et al., 2005; Lomba et al., 2010). Further, incomplete information on their distributions, often gathered over long periods of time and with limited spatial accuracy, makes the assessment of these species particularly challenging (Engler et al., 2004; Lomba et al., 2010; Gogol-Prokurat, 2011; Marcer et al., 2013). Consequently, and according to the International Union for Conservation of Nature (IUCN) guidelines, the estimation of the extent of species distributions constitutes the core of most assessment schemes (IUCN, 2001). Even if both Article 17 and Red Listing aim to assess the conservation status of species and habitats, they rely on related but rather distinct criteria. Article 17 of the Habitats Directive places particular emphasis on the assessment of species ranges and areas of potentially suitable habitat (ETC/BD, 2011). In former reporting periods, the standard approach to determine a species' distribution was the minimum convex polygon (MCP; (IUCN, 2001)), and as a result the quality of reported ranges wan uneven (Urda and Maxim, 2012). More recently, the European Topic Centre on Biological Diversity (ETC/BD, 2011) developed a tool to make the assessment of the conservation status for European biodiversity features easier and more accurate. Known as *Range Tool*, it computes the range for the selected species or habitat types and creates standardized outputs that could be used for the reports on the implementation of the Directive (Maxim, 2013). On the other hand, the IUCN has recently recommended the development of techniques that better reflect threats to species' persistence than those from predicted range changes, emphasizing the potential of species distribution models (IUCN, 2011; Fordham et al., 2012). Moreover, European Union (EU) guidelines highlight modeling the habitat used by a species and its potential suitable habitat as an important tool for periodic assessments and reporting (ETC/BD, 2011).

Species distribution models (SDMs; Guisan and Zimmermann, 2000; Guisan and Thuiller, 2005) are being increasingly used to inform monitoring programs and thus conservation policies (Guisan et al., 2013). These models have been successfully applied to locate new populations of rare and threatened species (e.g Guisan et al., 2006), prioritize areas for conservation (e.g. Carvalho et al., 2011), evaluate potential effects of global change in species distribution (e.g. Thuiller et al., 2005), and to infer extinction risk of species (e.g. Benito et al., 2009). In such context, climate change has been considered one of the major drivers of species distributions at a large spatial extent (Pearson et al., 2004; Soberón and Nakamura, 2009; Bellard et al., 2012) and species are assumed to be mainly constrained by their physiological tolerance to temperature and humidity. Land-use changes have also been assessed as they may affect biodiversity and ecosystem services at several relevant scales, from wide assessments across Europe (e.g. Reidsma et al., 2006; Verburg et al., 2006), to local studies of landscape-level changes of biodiversity (e.g. Lomba et al., 2012; Pompe et al., 2008). Thus, anticipating the combined impacts of climate change and land-use, which can lead to dramatic declines in biodiversity, is critical to prioritize conservation planning and effectively protect biodiversity under conditions of environmental change (Riordan and Rundel, 2014).

Supported by the growing availability of data and from conceptual and technical advances in SDMs, there is an emerging recommendation to simultaneously apply several methods (ensemble modeling; Araújo and New, 2007) within a consensus modeling framework (Thuiller, 2004; Marmion et al., 2009). Such cutting-edge modeling framework is known to reduce the predictive uncertainty of single-models by combining their predictions (Buisson et al., 2010; Grenouillet et al., 2011), thus increasing the accuracy of species distribution forecasts (Marmion et al., 2009).

In this paper, we investigate SDMs as tools to provide relevant information needed for reporting under the Article 17 of the Directive. To approach this issue, we present a tailored modeling framework to tackle the combined effects of climate and land-use changes on the distribution of focal species. Such framework is based on a multi-scale approach that acknowledges that different factors act more strongly at different spatial and temporal scales (Wu and Smeins, 2000; Pearson et al., 2004; Milbau et al., 2008). At a regional scale, climate strongly influences the distribution and abundance of plant species, while at local scales, topography and soil typically become important in influencing floristic variability (Pearson et al., 2004; Luoto et al., 2007; Milbau et al., 2008; Riordan and Rundel, 2014). We illustrate our modeling approach with *Veronica micrantha*, an Iberian endemic plant listed in Annex II of the EU Habitats Directive. As the distribution of *V. micrantha* remains poorly understood, SDMs were considered an ideal tool for predicting locations of additional, as of yet unknown, populations (Guisan et al., 2006). This work explores the potential of this novel modeling approach for the assessment of the distribution of rare and endangered species in the context of the EU Article 17 report, in the line of Attorre et al. (2012) and Marcer et al. (2013). We described the general approach and compared it thereafter to the range estimate provided by convex polygons and range maps generated using the latest *Range Tool*. Further, we performed a sensitivity test to the proposed framework to assess whether it is able to capture the effects of future environmental changes on the potential suitable habitat available for *V. micrantha*. The results are discussed in light of their influence upon the development of adequate conservation strategies and implications for conservation.

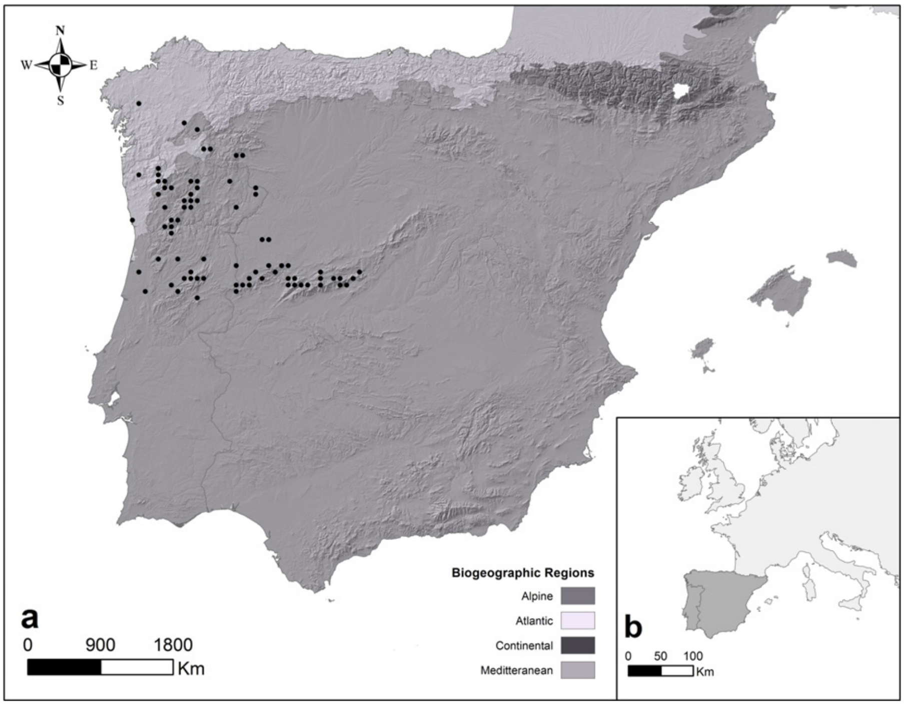

Fig. 1. Biogeographical regions in the Iberian Peninsula. Known occurrences of the test species (a) and location in the European context (b) are also presented.

2. Methods

2.1. Study area, test species and distribution data

The study area is the Iberian Peninsula as the test species is an Iberian endemic plant (Peraza Zurita, 2011). The Peninsula covers ca. 588 200 km^2 of area and includes three different Biogeographical regions: Mediterranean, Atlantic and Alpine (Fig. 1; European Environmental Agency, 2005). In short, the Iberian Peninsula consists of a compact land mass with asymmetrical distribution of major mountain massifs and characterized by a strong climatic gradient, from the rainiest and coldest areas with temperate climate in the north and northwest to the driest and warmest areas with Mediterranean climate in the south and southeast (e.g. see Lomba et al., 2010). The Mediterranean region encompasses almost the entire surface of Portugal and Spain (88.1% of the study area), and constitutes one of the main hotspots for biodiversity within the Mediterranean Basin, acknowledged to host high levels of plant diversity and endemism (Myers et al., 2000; Rodríguez-Sánchez et al., 2008; Pascual et al., 2011).

Veronica micrantha Hoffmanns. & Link is an herbaceous perennial plant from the Scrophulariaceae family, endemic to the northwest quadrant of the Iberian Peninsula (Martínez-Ortega et al., 2009). *Veronica micrantha* has been reported as occurring in open spaces of deciduous forests, heaths and herbaceous communities of forest fringes, preferring shaded biotopes with humid soils (European Commission, 2009). Due to the current restricted geographic distribution, specific ecological needs, and small and highly fragmented populations, the targeted plant species is considered a Vulnerable (VU) taxon (Olivieri and Vitalis, 2001; Bilz et al., 2011). Furthermore, regressive trends have been observed in its distribution, population, and extent and quality of its habitat (Peraza Zurita, 2011). The species is considered of high conservation interest and is covered by legal protection under the European Habitats Directive (EU Directive 92/43/EEC; Annex II).

As data on current distribution and habitat requirement for this species is lacking, records for *V. micrantha* were gathered from herbarium collections and the "Proyecto Anthos" (Real Jardín Botánico, 2011), a project developed to gather and record the results of the ongoing work of Flora Iberica (Castroviejo, 1986–2013). These data were complemented by distribution data from the Habitats Directive Reports (European Commission, 2009), as well as from fieldwork performed during the year of 2011. All data were aggregated into 10 $\times$ 10 km^2 grid cells and mapped using ArcGIS v. 10.1 (ESRI, 2013). Only observations with geographic accuracy equal to or better than the resolution of environmental predictors were used, but ensuring that the whole geographic and environmental range of the species was represented in the final dataset. The final database consisted of 77 observations: (1) 46 from the Anthos project, (2) 45 from the reports on Article 17, and (3) 21 from fieldwork.

Table 1
Predictors selected to model habitat suitability for *Veronica micrantha* in the Iberian Peninsula, assigned to regional versus local scales of variation, and grouped into climate and landscape related groups of predictors accordingly.

Predictor	Description	Source
Regional scale–Climate		
T_{Ann}	Annual Mean Temperature	WorldClim (2013, http://www.worldclim.org/current)
T_{Seas}	Isothermality	
T_{WetQ}	Mean Temperature of the Wettest Quarter	
P_{Ann}	Annual Precipitation	
P_{Seas}	Precipitation Seasonality	
P_{WarQ}	Precipitation of the Warmest Quarter	
Local scale–Landscape		
pUrba	Percentage (%) cover of Urban Fabric	Corine Land Cover 2000 (2013, http://www.eea.europa.eu)
pArab	Percentage (%) cover of Arable Land	
pCrop	Percentage (%) cover of Permanent Crops	
pAgri	Percentage (%) cover of Heterogeneous Agricultural Areas	
pFore	Percentage (%) cover of Forests	
pHerb	Percentage (%) cover of Scrub and/or Herbaceous Vegetation	

2.2. Environmental data

To estimate the distribution of the species, the predictor variables were chosen in three steps. In the first step, as species distributions are driven by processes linked to several levels of ecological complexity, and therefore expressed at different spatial scales (Guisan and Thuiller, 2005), variables were classified as expressing either regional or local effects (see Vicente et al., 2011). Bioclimatic variables (19; Table A1 Appendix A) were obtained from WorldClim database (Hijmans et al., 2005), and future climate projections, calibrated and statistically downscaled using the WorldClim data for 'current' conditions (sourced from the 4th IPCC assessment report; Bernstein et al., 2007). For this research, Hadley Centre Model (HadCM3;Gordon et al., 2000) data was employed for the time intervals 2020 and 2050. HadCM3 is a global climate model developed at the Hadley Centre of the Met Office in the UK. The IPCC A2 scenario was chosen with the assumption that, in the future, there would be high population growth coupled with slow economic growth and extensive technological change (Nakićenović and Swart, 2000). For land cover, variables were constructed by aggregating level 3 CORINE Land Cover classes and respective percentage coverage within each 100 km^2 grid cell, resulting in 14 variables (Table A1 Appendix A). Data derived from the CORINE Land Cover (CLC) Map 2000 (EEA, 2000, 2002) were aggregated into 10×10 km^2 grid cells, in agreement with the standard resolution required by Article 17 of the Habitats Directive to submit species distribution data (ETC/BD, 2011), and mapped using ArcGIS v. 10.1 (ESRI, 2013). In the second step, all variables were tested for pair-wise correlations based on the Spearman's rank correlation coefficient to minimize both collinearity and number of predictors (Jiménez-Valverde and Lobo, 2007) (see Table A1 in Appendix A for a detailed description). As described in Raedig and Kreft (2011), only predictors exhibiting three or less high correlations ($r \geq |0.6|$) were considered for modeling species' range. In the third step, we used expert knowledge and existing literature (Martínez-Ortega et al., 2009) to select the predictors known to determine the targeted species distribution. The final set of predictors included 6 climatic variables (hereafter regional predictors) and 6 landscape variables (hereafter local predictors) (Table 1).

2.3. Modeling framework

Our modeling framework aims to demonstrate SDMs utility for reporting on plant species of high conservation interest, such as many of those listed under EU's Habitats Directive. First, we used a SDM approach to model species current and future suitable habitat, combining regional and local models, following an approach similar to that described by Vicente et al. (2011). As a result, an environmental suitability map was constructed using a combination of GIS map layers based on habitat (land use data; see Fig. B1 in Appendix B for details) and climate (see Fig. B1 in Appendix B for details). The results of these relative suitability layers overlaid together to create a combined environmental suitability map. Climatic maps were produced from current (2000) and projected future (2020 and 2050) climatic data, allowing us to include a dynamic change in climate suitability. The land use/land cover map was assumed to remain unchanged in the future, because dynamic land use variables are currently of lower interest to model distribution shifts with climate change due to the acknowledged low resolution and the low level of thematic information of the available land use change scenarios (Martin et al., 2013).

Additionally, and according to the assumption that the estimate of range may exclude discontinuities or disjunctions within the overall distributions of a species (e.g. large areas ecologically not suitable; ETC/BD, 2006), we only considered as suitable those areas where the species is currently present and not isolated from other areas that do contain records by a barrier of unsuitable habitat (as defined by the models) in neighboring cells. Due to the large cell size, this neighborhood dispersal was defined and limited to the eight immediately adjacent cells following Hogeweg (1988). Whilst this value was assumed to be adequate for our test species, our approach assumes that such value may vary for other taxa and/or geographic contexts, as long as built on the characteristics of the targeted species.

2.4. Model fitting and evaluation

We used the BIOMOD package, implemented in the R software (R Core Team, 2012), for fitting SDMs. BIOMOD allows combinations of several modeling techniques in an ensemble forecast framework (Thuiller et al., 2009). All the ten modeling techniques currently available in BIOMOD were implemented (GLM, GAM, CTA, ANN, SRE, GBM, RF, MARS, MDA and MAXENT), with default parameters. In the lack of absence data, the use of pseudo-absences has been adopted since it is considered sound and allowed us to make use of a wide range of algorithms (Engler et al., 2004; Wisz and Guisan, 2009; Barbet-Massin et al., 2012). Therefore, pseudo-absences have been randomly selected from the studied area excluding available presence points (using the BIOMOD package in R). A total of random 770 cells were chosen (10 times the number of confirmed presences; Chefaoui and Lobo, 2008) from the 5805 cells of the background data. The predictive performance per variable was assessed using a randomization procedure as implemented in BIOMOD (Thuiller et al., 2009).

As no independent data existed to evaluate the predictive performance of the models, available data were randomly divided into two subsets: 80% of the data (presences and pseudo-absences) were then used for model calibration, and the remaining 20% used for model evaluation (e.g. see Araújo et al., 2005). The procedure was replicated 100 times. To obtain a measure of the accuracy of the SDMs the AUC of the ROC was used. This measure is not only threshold independent but also evaluates both the false-positive error rate and the true positive rate in order to obtain a measure for the accuracy of the constructed model (Elith et al., 2006). AUC values range from 0 to 1, with values below 0.5 representing a model that is not better than random and values of 1 represent models that are highly accurate. Although this metric has been criticized in some recent studies (Lobo et al., 2008; Jiménez-Valverde, 2012), it is still the most applied measure of accuracy for SDMs and that is why we considered it for our analysis. And, further, the AUC statistic was found to be reliable to compare models generated for a single species in the same area and the same predictors (Fourcade et al., 2013). For the final ensemble forecasting, only models with AUC above 0.7 were used. This threshold was also used to convert the projected occurrence probabilities into presence/absence predictions per grid cell, based on the recommendations of Elith et al. (2006) that values between 0.7 and 0.75 are considered potentially useful. Percentage of presences and absences correctly predicted (sensitivity and specificity) are also provided. Sensitivity reflects a model's ability to correctly predict a presence at a location and specificity reflects a model's ability to correctly predict an absence at a given location (Freeman and Moisen, 2008a).

Partial models were fitted using either climate or land-use types as the only predictors. Combined models were then developed from the spatial combination of the predictions resulting from these models (Vicente et al., 2011). Finally, AUC and calibration statistics (sensitivity and specificity) were calculated using the 'PresenceAbsence' R package (Freeman and Moisen, 2008b). The AUC of the combined model was computed after combination of the two partial models.

2.5. Range Tool and convex hulls

The *Range Tool* (http://bd.eionet.europa.eu/activities/Reporting_Tool/Reporting_Tool_Software) generates grid-based distribution and range maps, based on the locations of confirmed sightings/occurrences, by a process whereby gaps in the distribution below a specified distance are filed (for a 10×10 km reference grid, the default number is '5' grid cells; see Urda and Maxim, 2012 for more details). The tool also provides a method for excluding from the range locations where certain species or habitat types cannot extend. Optionally, the tool can also make use of the data reported by Member States regarding the occurrence of particular species or habitats in Natura 2000 sites.

The MCPs were generated running a Bounding Containers Python script (Patterson, 2010) to create a rectangular feature class with the same grain size (10 km^2).

3. Results

3.1. Suitable habitat and its dynamics

Climate and land-use data were combined to achieve a more informative model regarding the distribution of suitable habitat for the target species. Three distinct types of models were sequentially obtained: (i) partial regional models (R), fitted with climatic predictors only; (ii) partial local models (L), fitted with landscape related predictors only; and, (iii) combined models, resulting from the spatial combination of the two previously described partial models (for more details see Fig. B1 in Appendix B). The average AUC of the two partial models was high and ranged from 0.921 ± 0.009 (L) to 0.967 ± 0.004 (R). Sensitivity values ranged from 0.714 ± 0.052 (L) to 0.870 ± 0.039 (R). Specificity was always higher than sensitivity and ranged from 0.890 ± 0.004 (L) to 0.920 ± 0.004 (R). The most important climatic variable was Precipitation of the Warmest Quarter (PWarQ). Overall, precipitation-related predictors were found to be more important than those related with the temperature regime. In the local partial models, the Percentage Cover of Arable Land (pArab) was identified as the most important landscape variable (for more details see Fig. C1 in Appendix C).

Under current conditions, most of the known occurrences of the test species were coincident with modeled areas where both regional conditions and local landscape attributes were predicted to be suitable. Nonetheless, there is a rather considerable overlap of the known occurrences with predicted areas with suitable climatic conditions but lacking adequate local habitats (Table 2). This final model attained a final AUC value of 0.810 ± 0.027 (sensitivity $= 0.649 \pm 0.055$ and specificity $= 0.972 \pm 0.002$).

Table 2
Distribution of the known presence records across the spatially combined projections of the regional and local partial models, for the several considered years. The numbers in bold correspond to areas where the species has both regional and local habitat suitable.

		Regional conditions		
		Suitable	Unsuitable	
Local conditions	Suitable	**50**	5	2000
		49	6	2020
		40	15	2050
	Unsuitable	17	5	2000
		17	5	2020
		11	11	2050

Fig. 2. Potential suitable habitat for *Veronica micrantha* under current (2000) and future (2020 and 2050) conditions.

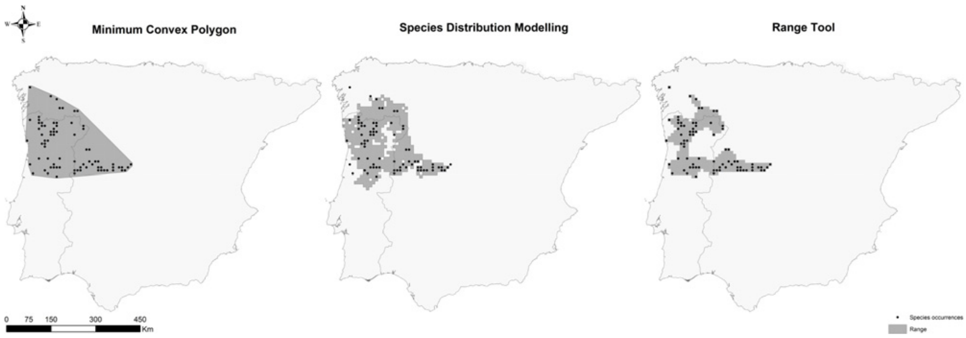

Fig. 3. Range of *Veronica micrantha*, as measured by minimum convex polygon, species distribution modeling and Range Tool, under current conditions.

Fig. 2 shows the predicted climatically-driven changes in potential habitat for *Veronica micrantha* between years 2000 and 2050. Areas without change are predominant, with only slight differences also observed between years 2000 and 2020. The highest decrease in potential habitat is projected for 2050. Under the A2 scenario the climatically suitable areas would diminish to around 17 000 km^2 (loss $=$ 21.5%), a very substantial reduction in its potential suitable habitat for a species already considered vulnerable. This means that from the current situation (21 400 km^2), the area of potentially suitable conditions is predicted to drop to 16 800 km^2 by 2050. Only in a few localities (represented as the darkest colored grid cells in Fig. 2) the suitable area is forecasted to increase (60 km^2 by 2020 and 40 km^2 by 2050). Overall, the most suitable areas were predicted to occur in the north-western quadrant of the Iberian Peninsula.

3.2. Range and its dynamics

The methods used to assess the range size differed considerably and, expectedly, so did the results (Fig. 3 and Table 3). The MCP resulted in the largest area, whereas assessments based on the Range Tool (33 100 km^2) were smaller than both the modeled range (48 900 km^2) and the convex polygons (69 469 km^2). The overlap between the different assessments tools is estimated to be 28 894 km^2.

Table 3
Predicted range for *Veronica micrantha* obtained from the minimum convex polygon (MCP), species distribution modeling (SDM) and *Range Tool* approaches under present and future (2050) conditions. Range size, measured using the *Range Tool*, was analyzed considering all known occurrences (a); and only those at predicted suitable areas under current (b) and future (c) conditions. All areas are expressed as km^2. n/a stands for not applicable and expresses the fact that future occurrences cannot be ascertained.

	Range	
	2000	2050
MCP	69 469	n/a
SDM	48 900	37 800
Range Tool	33 100(a)	n/a
	29 400(b)	25 300(c)

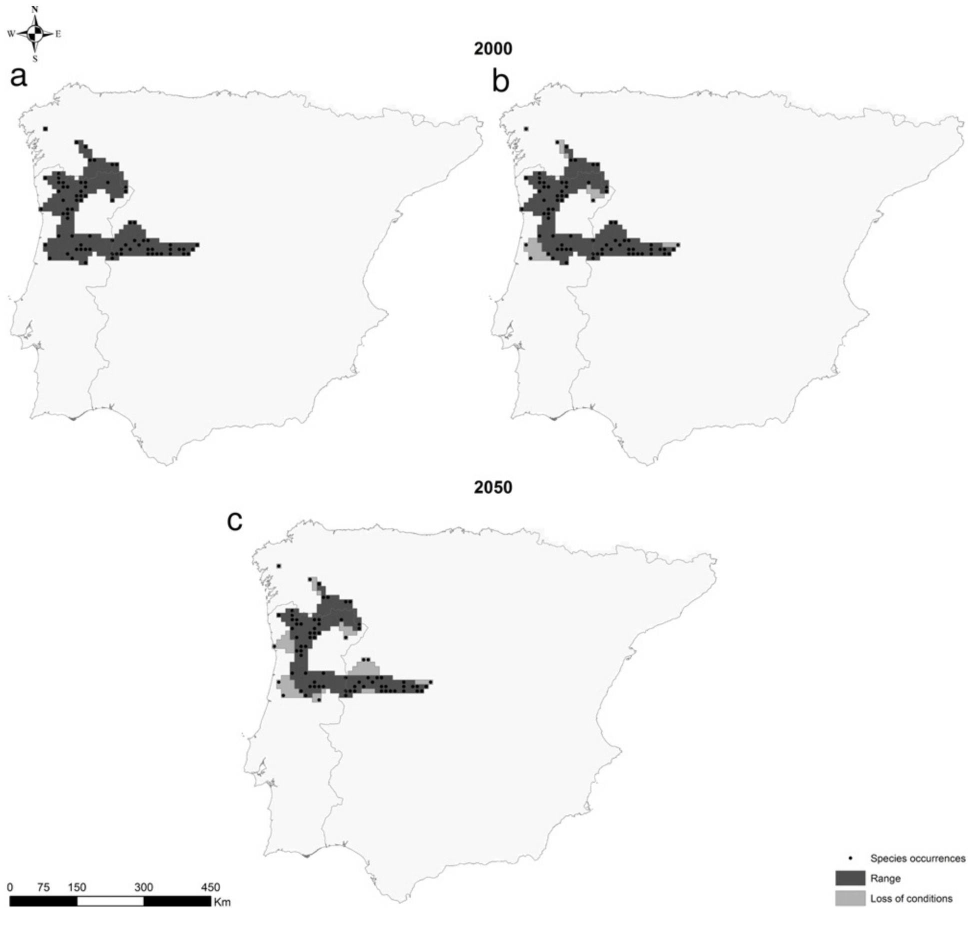

Fig. 4. Range of *Veronica micrantha*, as calculated by range tool, under current conditions. Range size assessed by considering all known occurrences (a), using only those occurrences at suitable areas (b) under current conditions, and using only those occurrences at suitable areas under future (2050) conditions (c).

The modeled range matches most of the known species' distribution. Further, additional areas which appear to be climatically suitable for *V. micrantha* but were not recorded as having the species were also highlighted. Overall, we suggest that at least some of these areas should not be interpreted as indicating model commission error, but rather that the species has still not been recorded in those areas.

Even when comparing range sizes derived from the same method, e.g. Range Tool, different data sets lead to rather distinct maps of species distribution (Fig. 4). If we take into account only the species' records in areas identified by the models as suitable, under current conditions, the range size is expected to decrease by more than 10%. For 2050, the expected decrease in range size rises to 15% (Table 3).

4. Discussion

4.1. Comparison of assessment methods

It is widely acknowledged that the method chosen to construct a species ranges has a great impact on the way the patterns and dynamics of species distributions are interpreted (Gaston and Fuller, 2009; Bombi et al., 2011; Raedig and Kreft, 2011; Maycock et al., 2012). The application of the minimum convex polygon (MCP) method is a very simplistic approach, and it is not able to provide better reliability than the more complex approaches, such as species distribution models (SDMs). As was already mentioned, an additional constraint to this approach is the overestimation of ranges, which is particularly high for species that exhibit a patchy distribution related to specific habitat conditions, such as *Veronica micrantha* (cf. Fig. 3 and Table 3).

The Range Tool was specially developed for the 2013 reports to the EU (Art. 17 Habitats Directive). The main advantage of this new tool is that it allows Member States to submit comparable, standard reports every regular reporting cycle, making the assessment of species and habitats easier and more reliable (Maxim, 2013). The reporting tool is especially useful for delineating habitat cores and gives a good fit to the realistic range estimate (cf. Fig. 3), since its core area is the smallest among the three. However, the Range Tool does not directly give any information on whether or not a site is suitable for the species, neither allows to anticipate future shifts in the distribution of species resulting from environmental changes such as climate or land use shifts. This has important implications for establishing conservation policies and monitoring programs for endangered plant species or others with specific ecological requirements. Nevertheless, the tool undoubtedly represents a positive step in the EU's strategy towards harmonization and integration of data at the European level.

4.2. Suitable habitat and its dynamics

SDM is currently the main method for predicting species distributions, which in turn may guide conservation management actions. In addition, the IUCN has recently begun to explicitly incorporate SDMs to estimate extents of occurrence as a parameter of risk of extinction and to explore potential impacts of climate change on species distribution (Cassini, 2011). Here we have used a combined modeling methodology to describe the potential distribution of the test species. Using this approach we have been able to integrate both regional-scale drivers of environmental change, such as climate, and local-scale drivers of land-use, to present a better understanding of the dynamics of the species. This is in agreement with previous studies showing that climate and land-use changes affect the species distributions at different scales (Lomba et al., 2010; Vicente et al., 2011; Riordan and Rundel, 2014). However, caution must be adopted in interpreting these results because the spatial scale at which the environmental data are represented may influence the modeling results. Here, we used a 10×10 km resolution, built on a grid system, as it is the standard resolution required by Article 17 of the EU Habitats Directive to submit the distribution data (ETC/BD, 2011). Also, the majority of our records have a grid reference of 10 km resolution. Additionally, the available land-use data for the Iberian Peninsula (i.e. CLC) is not compatible with higher resolutions. Even if there is spatially explicit national information on land cover for Portugal and Spain, these datasets were produced with different objectives and using different methodologies. As a result, they differ in scale, nomenclature and minimum mapping unit, among other factors, proving to provide unreliable results, as it would increase the error added to our models.

With this in mind, we built combined models, which accord with the current known geographic distribution of the target species and provide comprehensive maps of the potential distribution in areas where records are scarce or non-existent. By considering a wider variety of potential species responses, combined models are not only more informative about the nature of the factors determining species occurrence, but also in terms of the spatiotemporal dynamics of species distribution, through the recognition of areas where the conditions for the species may (or may not) deteriorate with climate and/or land-use changes (Vicente et al., 2011). For our studied species, climate change will worsen the current already poor representation of the species (cf. Fig. 2). Our results revealed that 20% of their climatically suitable habitat is predicted to be lost as a result of climate changes projected for 2050. The estimates we made, even though already worrying, might be considered optimistic, since, at larger grain sizes, coarser representations of species distributions may overestimate the local availability of suitable habitats (Rondinini et al., 2006). This is especially true for rare species, which typically have a patchy distribution constrained by the local availability of suitable habitat (Williams et al., 2009; Gogol-Prokurat, 2011). In addition, our results indicate that it is unlikely that this species will be found much beyond its currently known range, but with one exception. Our partial regional models predicted a small area of suitable habitat in the Sierra Nevada region (southern Spain; see Fig. B1 in Appendix B for details on excluded grid cells). However, is highly unlikely to find our target species there because, on one hand, *Veronica micrantha* is known to be endemic to the north-western of the Iberian Peninsula; and, on the other hand, the Sierra Nevada flora has been extensively cataloged and descripted in detail for many years (e.g. Blanca et al., 1998). For these reason, these areas were excluded from the calculated range (see Section 2.3 for an explanation of the modeling framework).

Indeed, the more informative character of this model-based approach proves to be particularly advantageous for conservation planning targeted at endangered species. First, the areas modeled as being environmentally suitable for the species, but not covered by existing records will provide the basis for stratifying sampling and improving datasets on rare and endangered species (Guisan et al., 2006). Second, the modeling approach will be valuable to confirm or reject species susceptibility to environmental change, and it will provide a more accurate picture of the impacts of environmental shifts on biodiversity in the future, at both national and European levels. Specifically, the results of a SDM assessment can be used to conduct consistent monitoring schemes and collect valuable data interest, which is particular relevant under conditions of data scarcity. Such is certainly important for when the periodic assessment and reporting process is next repeated, in 2019. Indeed, for *V. micrantha*, like other species with a low abundance population, or with a low overall detectability, the strength of this approach is that it can be applied in situations where management decisions must be based on limited information.

4.3. Remaining challenges and future perspectives for reporting

Although we were able to adequately estimate the areas that the species could potentially inhabit, there is still room for improvement. The application of this approach needs to be tested further on a larger number of scenarios, regions and test species, in order to evaluate its reliability. One possible way to overcome this issue may be to use virtual data to test the effects of different aspects of modeling on the prediction accuracy of SDMs (Hirzel et al., 2001; Meynard and Kaplan, 2013). Simulated species data have the advantage of providing perfect knowledge and control over the underlying processes that drive real species distributions. However, this approach is not yet fully explored and even if a method works well in the virtual world, this does not guarantee that it works in the real world as well. The real world is much more complicated, and conclusions drawn from the virtual datasets might be limited, specifically when discussing rare or endangered species (Zurell et al., 2010). Additionally, SDM-based simulations often assume a changing climate but unchanged land use to estimate future species distribution shifts (Martin et al., 2013). The joint inclusion of land use and climate change scenarios should be considered to support a more comprehensive forecast of the species trends. Uneven availability or quality of environmental data also emerges as a hindrance to assessing the status of this species. If the goal is to improve the information that will be submitted in the next reporting cycles, environmental data (e.g. topographic, climatic and land-use data) with better spatial and/or temporal resolution and increased accuracy is of key importance. Finally, a careful assessment of the modeling results should be made, particularly in the cases of endangered species. For example, predicted presence areas that are isolated from observed occurrence records by a dispersal barrier may be removed, whereas sites where the species occurs, but are not predicted by the models may be incorporated. On this matter, a detailed analysis of the 8-neighbor cells rule's conservation implications would configure a very important research. There are different kinds of simple neighborhood to consider such as the 4 cell von Neumann in contrast to the 8-cell Moore neighborhood. All these give rise to many possibilities but the neighborhood used in most ecological studies, including in landscape and species distribution models (see e.g., Pausas, 2003; Thomas and Moloney, 2012), is the 8-cells adjacent to the target cell. It is more efficient and leads to more even species distributions. However, this value may be modified for example dependent on dispersal and migration potential of a species, but has to be fixed for each species once for future reporting (ETC/BD, 2011).

Notwithstanding this, the approach described here proved useful for modeling the potential distribution of this species. Its relative ease of implementation and low requirements in terms of information is ideal for the assessment of a species, namely for rare and/or endangered ones. In this regard, it must be acknowledged that modeling results are not an end in themselves, but rather a potentially valuable tool to the enhancement of conservation planning and monitoring programs.

5. Conclusion

Overall, our results highlight the usefulness of SDMs to report on rare species, and illustrate how the tool applied to such reporting assessments may affect decisions about resource allocation for monitoring and conservation. We consider the statistical modeling of the potential distribution of target species a more adequate estimate of the available suitable habitat for the focal species and thus a useful tool to complement existing data. Also, as the effects of climate and land-use changes on species distributions become more noticeable, those effects should be considered in the next assessment and reporting periods. This further highlights the importance of this novel framework for future assessments of threatened species and habitat types in a global change context. As a result, the proposed approach might be of interest for scientists and managers dealing with rare and endangered species.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at http://dx.doi.org/10.1016/j.gecco.2014.09.011.

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